Thought of Search: Planning with Language Models

Through the Lens of Efficiency

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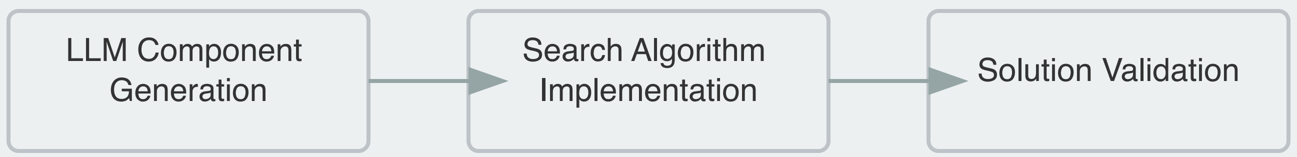
Problem Statement

Current LLM-based planning methods lack soundness, completeness, and efficiency.
How can we improve these aspects while maintaining high accuracy?

Methodology: "Thought of Search" Approach

1. Use LLMs to generate search components (successor functions, goal tests)
2. Implement standard search algorithms (e.g., BFS, DFS) with generated components
3. Ensure soundness and completeness through component validation
4. Minimize LLM calls to improve efficiency and reduce environmental impact



Key Takeaways

1. "Thought of Search" outperforms existing methods in efficiency and accuracy
2. Maintaining soundness and completeness is crucial for reliable AI planning
3. Reducing LLM calls significantly lowers computational costs and environmental impact
4. The approach is versatile, applicable to various search problems
5. There's a need for more responsible use of computational resources in AI research

Results and Findings

- Achieved 100% accuracy on tasks like 24 Game, Mini Crosswords, and BlocksWorld
- Significantly reduced number of LLM calls compared to existing methods
- Maintained soundness and completeness in search algorithms
- Improved computational efficiency and reduced environmental impact

Method	LLM Calls	Accuracy	Soundness/C
Thought of Search	Few (≈2-3)	100%	Maintained
Existing Methods (e.g., ToT)	Many (≈100+)	75-95%	Not guaranteed

Limitations and Future Work

Limitations:

- Assumes rule conditions involve single facts, limiting real-world applicability
- May face challenges in scaling to more complex, large-scale problems

Future Work:

- Automate component validation to reduce human intervention
- Extend the approach to handle multimodal inputs and complex interdependencies
- Investigate integration with heuristic functions for improved scalability